DEVELOPMENT OF A COMPRESSION ALGORITHM SUITABLE FOR EXERCISE ECG DATA

K. Uyar[1], Y. Z. Ider[2]
[1]Department of Electrical and Electronics Engineering, Middle East Technical University, Ankara, Turkey
[2]Department of Electrical and Electronics Engineering, Bilkent University, Ankara, Turkey

***Abstract*- Huge amount of data recorded during exercise electrocardiography may be stored for further analysis or be transferred to a remote physician through telephone lines. Due to channel limitations, data must be compressed prior to the transfer. In this study, an algorithm suitable for compression of exercise electrocardiography data is proposed. 2-D Discrete Cosine Transformation is applied in the algorithm to make use of the pseudo periodic behavior of the data. To increase the correlation, data is aligned from the R peaks. QRS detection is performed using Fast Dyadic Wavelet Transform. The success rate of the detection algorithm is found to be 99.78%. Uniform scalar quantization is used with zonal coding method in the coding of 2-D Discrete Cosine Transform coefficients. The performance of the compression algorithm is evaluated in terms of compression ratio, reconstruction error and by comparing the reports of the ST segment depression test applied before the compression and after the reconstruction to inspect whether vital information is preserved.**
***Keywords* - exercise electrocardiography, compression, discrete cosine transform, dyadic wavelet transform**

I. INTRODUCTION

Exercise electrocardiography (ECG) is one of the most important and valuable non-invasive diagnostic test in the clinical evaluation and management of patients with suspected or known cardiovascular disease, particularly coronary artery disease [1]. Exercise ECG can also provide valuable information in evaluating the functional capacity of patients and in evaluating the efficiency of surgical/medical therapy.

Telemedicine is the use of telecommunications technology to provide healthcare services to patients who are geographically separated from a physician or other healthcare providers. In a telemedicine system, some vital information such as x-ray image, ECG signal, heart sound etc. is sent to the remote physician to let him make a decision about the patient's health without seeing him physically. In many cases, the datum that carries vital diagnostic information requires a vast amount of space for storage and long transmission time to reach the physician. For instance, a typical 12-lead exercise ECG data that last 21 minutes with a sampling rate of 1000 samples/sec and a resolution of 16 bits/sample requires a storage space of 28.8MB. Transmission of this raw data through a channel of 33.6Kb/sec lasts 2 hours. Limitations on storage space and transmission time require the compression of the transmitted data.

In biomedical data compression, the clinical acceptability of the reconstructed waveform is usually determined through visually inspecting those critical points or areas that contain more clinical information to the physicians. Here lie the weak and strong points of lossy compression techniques. They can compress more than lossless algorithms. However, some of the vital information is lost.

Recent compression algorithms involve transform coding. In these algorithms, data to be compressed are transformed to another domain and compression is applied on the transformed data set itself. Reconstruction is done by decompressing the compressed data and backtransforming to the original domain. An approach is the Karhunen-Loeve Transform (KLT). In the KLT approach [2], eigenvectors of the data autocovariance matrix are found and the ones that are associated with the largest eigenvalues are retaind. Blanchett reports a CR of 30:1. The major drawback of KLT is that, it is data dependent and requires heavy computation. Some other transforms used are Discrete Cosine Transform (DCT), Fourier Transform [3], and Wavelet Transform (WT) [4]. In these transforms, the energy is compacted to the coefficients with high magnitude. Thus, by storing only the coefficients that are greater than a threshold, compression is achieved.

The aim of this study is to present a compression algorithm suitable for compressing exercise ECG data while preserving the vital information.

II. METHODOLOGY

An ECG data set contains sample to sample correlation as well as beat-to-beat correlation. Thus, a 2-D transform coding scheme is used to handle the pseudo periodic behavior of the exercise ECG. In this study, DCT is used as the 2-D transform. The use of 2-D DCT requires the alignment of adjacent heartbeats to increase the beat-to-beat correlation. To align the adjacent heartbeats, the location of R peaks in the ECG data should be determined. This is accomplished by QRS detection. After R peaks are located, heartbeats are aligned to each other and a 2-D array is formed. 2-D DCT is

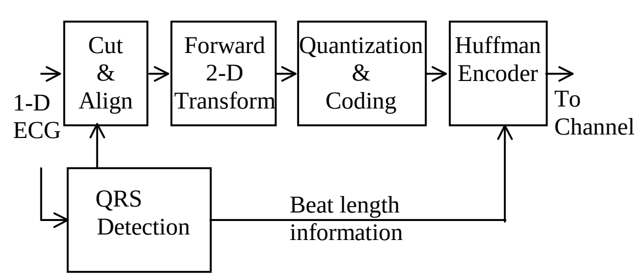

Fig. 1. Block diagram representation of the compression stage.

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applied to the raw data. Resulting transform coefficients are quantized and encoded. Coefficients are further compressed losslessly via Huffman coding and sent as compressed data. Decompression is straightforward. Received data are decoded via Huffman decoder and 2-D DCT coefficients are formed. Inverse 2-D DCT transform is calculated and 2-D ECG data array is reconstructed. As a final step, 1-D ECG data array is recreated from the 2-D array. The procedure is summarized in Fig. 1. Major concerns in evaluating the performance of the algorithm are; the compression ratio and the retaining of the vital information after compression-decompression of the data. For this purpose, exercise ECG ST segment depression test is applied to the reconstructed data and results are compared with the test results applied to the original data.

A. QRS Detection

QRS detection is done by Dyadic Wavelet Transform (DWT). The wavelet used in this study is a quadratic spline wavelet with compact support and one vanishing moment. It is the first derivative of a smoothing function [4]. In Mallat's work [4], quadratic spline wavelet is used for multiscale edge detection. It is expected that the
edge detection wavelet should detect QRS region well since this region contains the sharpest edges in the data. Scaling function $\psi(x)$ and the associated wavelet function $\phi(x)$ are given in Fourier domain as;

$$\Phi(\omega) = e^{-j\frac{\omega}{2}} \left(\frac{\sin(\omega/2)}{\omega/2} \right)^3 \tag{1}$$

$$\Psi(\omega) = j\omega \left(\frac{\sin(\omega/4)}{\omega/4} \right)^4 \tag{2}$$

A lowpass filter $H(\omega)$ associates the scaling function and the dilated form of the scaling function as shown in (3).

$$\Phi(2\omega) = \frac{1}{\sqrt{2}} H(\omega)\Phi(\omega) \tag{3}$$

Wavelet functions are associated to the scaling functions through a highpass filter $G(\omega)$ as in (4).

$$\Psi(2\omega) = \frac{1}{\sqrt{2}} G(\omega)\Phi(\omega) \tag{4}$$

Fast Dyadic Wavelet Transform (FDWT) of the 2-D ECG data set is calculated using the "algorithme a trous" as explained in [4]. At each level, data set is passed through the high pass filter to calculate FDWT coefficients and passed through the low pass filter to calculate the input data set for the next stage. At each level, filters are stretched as explained in "algorithme a trous". Fig. 3 shows the data in which the QRS region is to be found, and 2 levels of FDWT, namely data, d1, and d2. It is observed that at j^{th} level, R peaks correspond to the zero crossings of a minimum-maximum pair in FDWT with a delay of 2^j-2 points. That is, for level 1, delay is 2^1-1=0 points. For level 4, delay is 2^4-2=14 points.

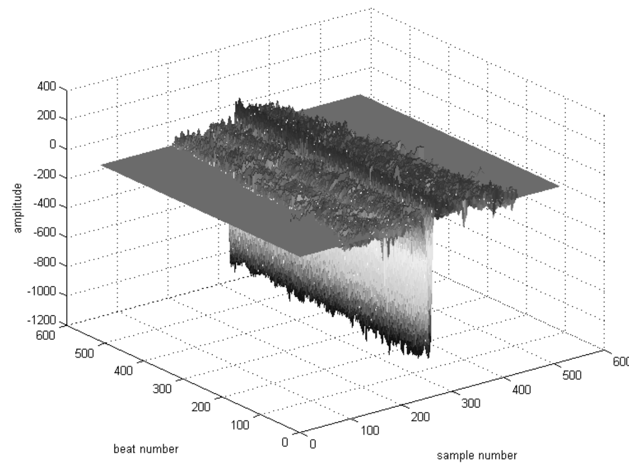

Fig. 2. ECG data set is aligned from R-peaks to form the 2-D array. 512 heartbeats are used in the creation process. Array is padded with zero in order to make the length of all heartbeats equal.

Thus, R peaks can be exactly located from any level transform, considering the delays.

B. Alignment and Discrete Cosine Transform

After the detection of R peaks, beats are aligned to each other from the R peaks in a column order to create a 2-D matrix as shown in Fig. 2. The reason for the creation of a 2-D matrix is to use the pseudo periodic behavior of the exercise ECG. The 2-D data in the matrix becomes more correlated than the 1-D form since sample to sample and beat to beat correlation can be inspected at the same time.

In the case of highly correlated data, Discrete Cosine Transform (DCT) is the optimum transform in terms of both

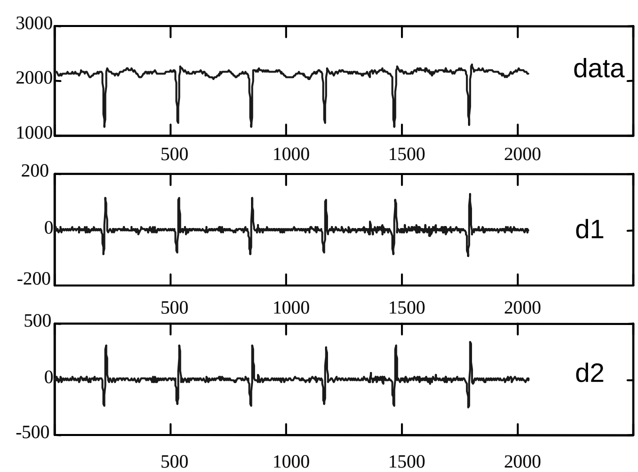

Fig. 3. Top figure shows 1-D ECG data. Middle and bottom figures show two level Dyadic Wavelet Transform, respectively. At each level, R peaks correspond to zerocrossings of a minima-maxima pair in DWT with a delay of 2^j-2 points.

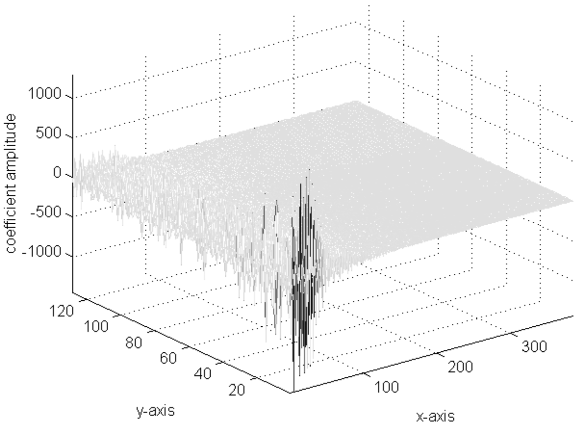

Fig. 4. 2-D DCT coefficients of the 2-D ECG array. Low frequency oefficients are greater than the higher frequency coefficients and contribute more to the reconstruction process.

energy compaction and computational cost. Moreover, DCT is data independent, i.e., basis functions are cosines at different frequencies and since they are known at the decoder side, they do not need to be transferred in a compression system. Thus, 2-D DCT is used in the compression algorithm.

In this study, the number of beats used to create a 2-D data matrix is chosen to be 128 after comparing the compression performances. Since DC value of each beat is different due to baseline change, DC values are subtracted from the data before the matrix is formed. Due to the fact that ECG is not strictly periodic in the mathematical sense, the lengths of beats are different. In order not to introduce a discontinuity, unfilled entries in each row are padded with zero to make the length of all the rows same. Irregular beats are not included in matrix generation and they are coded losslessly via Huffman coding as described later. DC values, starting and ending points of each beat are stored and coded in the same way. Then, 128-point 2-D DCT is applied to the 2-D data. Transformed coefficients are as shown in Fig. 4. Instead of applying to submatrices, 2-D DCT is applied to the per 128 beat data matrix only to overcome the effect of block size.

C. *Bit Allocation and Quantization*

After 2-D DCT is applied to the exercise ECG data, it is observed that the transformed coefficients have real values, and some coefficients are very high as compared to other coefficients. Smaller coefficients do not need to be represented with the precision that the higher coefficients are represented.

The quantization method is determined to be uniform scalar quantization in this work and is decided after the statistical results of different ECG data sets are examined. The examination of probability density function of DCT coefficients of many patient files used in this study revealed that, the DCT coefficients of a frame can be divided into 4 zones as shown in Fig. 5. A frame is defined to be every 128-beat DCT coefficient matrix.

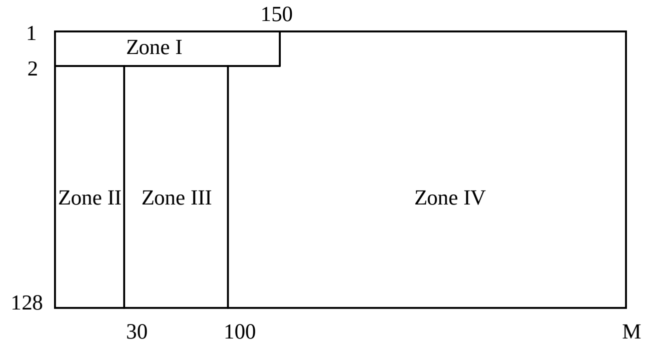

Fig. 5. Zones of a 128xM frame. DCT coefficient values decrease from Zone I to Zone IV.

The quantization in each zone is performed independently from the other zones. Since the distribution of coefficients in each zone changes from frame to frame, a uniform quantization table is used. As a result, uniform scalar quantization with zonal coding is preferred. A closely related problem is the bit allocation to the zones, which in fact determines the quantization step and the reconstruction error. In this study, the quantization step, Δ, is calculated for each zone in each frame to consider the rapidly changing characteristics of the exercise ECG data and is sent to the decoder for every zone and frame. Since Zone I contains the most important coefficients, they are sent near losslessly (i.e., Δ =1). Zone IV is not sent to the decoder side since the coefficients in that region do not contribute to the reconstruction much. Table I denote different compression types that correspond to different bit allocations to the zones mentioned.

TABLE I

ZONES IN A FRAME AND THE CORRESPONDING ALLOCATED BITS

Type	Zone I	Zone II	Zone III	Bit I (bps)	Bit II (bps)	Bit III (bps)
1	2 x 150	126 x 30	126 x 70	16	6	1
2	2 x 150	126 x 30	126 x 70	16	6	2
3	2 x 150	126 x 30	126 x 70	16	6	3
4	2 x 150	126 x 30	126 x 70	16	7	2

D. *Huffman Coding*

After DCT coefficients are quantized, these coefficients are further compressed losslessly via Huffman coding. The basic idea under the Huffman algorithm is that, the more frequent messages can be represented with shorter codes (less amount of bits) and less frequent messages can be represented with longer codewords. At the end of assigning bits to the messages, a look up table is created. The look up table is sent to the decoder and a decoding tree is generated at the decoder

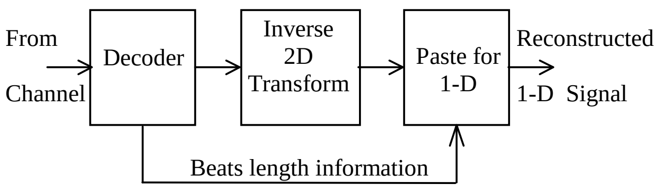

Fig. 6. Block diagram of the reconstruction steps.

side. Encoded data set is decoded instantly by constructing a binary tree as the datum comes. This lossless algorithm is applied to the quantized DCT coefficients and the irregular beats excluded in the analysis as well as to the DC values, starting and ending locations of every beat mentioned before.

E. *Reconstruction*

Reconstruction step is straightforward. Lossless encoded coefficients, irregular beats excluded in the transform, DC values of beats, starting and ending points of beats are decoded via Huffman decoder. 2-D coefficient matrix is formed. Inverse 2-D DCT is applied to calculate the 2-D data matrix. Considering the irregular beats excluded in the transform, DC values of beats, starting and ending locations of beats, 2-D data matrix is returned back to the original 1-D ECG data. This process is shown in Fig. 6.

III. RESULTS

Performance of the wavelet based QRS detection algorithm is evaluated in terms of the number of the heartbeats in an ECG data set and the number of the heartbeats found by the detector using (5).

$$\%\mathit{Success\ Rate} = 100 * \left(\frac{\mathrm{RB - FRB}}{\mathrm{RB}} \right) \qquad (5)$$

where RB: Regular beats present in the data

FRB: Regular beats found by the algorithm

The QRS detector rejected all the irregular beats in all of the 15 patient files successfully. Average Success Rate of the algorithm is found to be %99.78.

Compression results are evaluated with the criteria of compression ratio (CR) as in (6), percent root mean square difference (PRMS), and with ST Segment Depression Test.

$$CR = \frac{\#\text{ of bits used before the compression}}{\#\text{ of bits used after the compression}} \qquad (6)$$

The ST60 Trend Graphic produced by the test shows every 10-second average of the ST region amplitude found in the ECG data. The data to be used are evaluated with this test before the compression and after the decompression. Performance is evaluated by comparing the test graphics. Fig. 7 shows the ST60 Trend Graphic of a patient before the compression. Files that are compressed at types 1 and 2 did not produce the same ST60 graphics before the compression and after the decompression. Type-3 compression generally produced the same graphics with minor differences, whereas type-4 compressed files always give out the same graphics after the decompression. CR value for type-1 and type-3 is found to range from 10:1 to 12:1. Type-4 CR value ranges between 7.86:1 and 9.64:1.

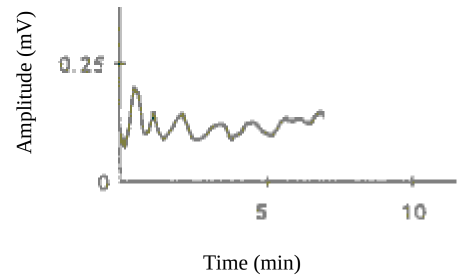

Fig. 7. ST60 graphic of the exercise ECG data for lead I. Every 10 seconds average of the ST segment amplitudes is shown.

IV. CONCLUSION

In this study, an algorithm suitable for the compression of exercise ECG is proposed. The study involved the detection of QRS region. A different detection algorithm based on Dyadic Wavelet Transform is used. This detection algorithm is found to be superior to classical techniques since it is immune to baseline change and can be implemented using fast filterbank algorithms.

Proposed method's results are evaluated using compression ratio (CR), reconstruction error, and ST depression test. In the study, four different compression levels are used. Zones that are mentioned previously are coded with 6-1, 6-2, 7-2, and 6-3 bit pairs. Test results reveal that the compression type-4 compresses the data such that, when reconstructed, the clinically important information is still kept intact. The compression success is judged by the similarity of the graphics produced by the test program. Types 1 and 2 generally failed the test. Type 3 mostly produced the similar graphics with some minor changes. Type 4 is the only compression type that produced the same graphics.

It is also concluded that, ECG leads I, aVF, and V_2 are more susceptible to loss of information during compression. The safe assumed type 4 compression yields results that range from 7.86:1 to 9.64:1 in the data set used. The term safe is judged via the graphics comparison results such that the vital information is preserved.

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